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An ILP approach for tactical flight rescheduling during airport access mode disruptions

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Abstract

Airport access mode disruptions, such as a subway shutdown, threaten the whole passenger door-to-door journey. When such a disruptive event occurs, knowledge on passengers' delays would help the airport operation centre to decide if a departure flight should be delayed. This paper proposes a tactical flight rescheduling at an airport to minimise the number of stranded passengers while considering operational constraints. An integer linear programming formulation of the problem is presented. Constraints such as terminal capacities, maximal runway throughput, minimum turnaround time, or minimum transfer time for connecting passengers are considered. An exact and a heuristic resolution are proposed and compared on a study case around Paris-Charles de Gaulle airport. The new schedule satisfies the operational constraints and reduces up to 60% the number of stranded passengers with moderate deviation from the initial planning.

Keywords: Air transportation; Flight rescheduling; Passengers; Access mode disruptions; Integer linear programming

1. Introduction

The European Commission, through the ACARE report, depicts a vision of how the transportation system should look like in 2050 (Commission et al., 2011). According to this one, “passengers [...] should enjoy efficient and seamless travel services, based on a resilient air transport system thoroughly integrated with other transport modes and well connected to the rest of the world”. To achieve this goal, the integration of the air and ground transportation systems is required. However, the lack of information sharing between air and ground transportation service providers remains an obstacle to an efficient and resilient air-ground integration. This is especially the case when passengers face a disruption during the first leg of their trips. For instance, when a subway shutdown occurs, passengers who rely on it to access

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the airport may miss their flights. Therefore, a delay experienced by a passenger on the first mode can lead to a significantly larger delay at his final destination. Bratu and Barnhart (2005) estimate that passengers missing their flights, who only account for 2% of the population, experience an average delay at their final destination of 303 minutes, accounting for 39% of all passenger delays. Thus, coordination at the tactical level between ground and air transportation service providers is crucial to mitigate the impact of such disruptions on passengers. Over the past few years, different European projects have been launched, such as MODUS (Paul, 2020), X-TEAM D2D (Bagamanova et al., 2022), IMHOTEP (Mota et al., 2020) or TRANSIT (Bueno et al., 2022) with a focus on door-to-door passenger journey.

The current study is part of the TRANSIT project. Here, we shed light on potential benefits for passengers obtained through information sharing between transportation stakeholders during an airport access mode disruption. We propose a formulation of the problem aiming at rescheduling flights at the tactical level based on information provided by ground transportation service providers. The objective relies in minimising the number of passengers missing their flights while taking airport constraints into consideration. In the following, we refer to the optimization problem considered in this study as the Passenger-oriented Flight ReScheduling Problem (PFRSP). A description of such a concept is presented in (Scozzaro et al., 2022a), where a simulated annealing algorithm coupled with a simulation-based evaluation is proposed to solve a first version of the PFRSP. Here, the problem has been enhanced through more detailed airport modelling and the consideration of additional operational constraints such as constraining priority flights to be on time. A linear problem formulation is proposed, enabling an exact-solving approach using an Integer Linear Programming (ILP) commercial solver. A heuristic based on a procedure that airport operators could follow is also designed to reschedule flights and to evaluate the relevance of an exact resolution approach. A data-driven approach integrating different data sets and statistics has been implemented to generate realistic instances around Paris-Charles de Gaulle airport. The contributions of this paper are the following:

1. A ILP formulation of the PFRSP. The model can be customised to prioritise either reducing the number of stranded passengers or limiting the total delay assigned to the flight set,
2. The integration of various data sets and statistics to calibrate an airport model and passenger behaviour (passenger transfer time, connecting passenger share, train schedules, passenger timestamps at security checkpoints, historical flight schedules, etc...),
3. A pool of instances available on a public repository through the reference (Scozzaro, 2023),
4. Detailed analyses of the results obtained on CDG case study. Sensitive analyses of the model depending on ILP parameters are presented to let operators tune the rescheduling tool depending on their objective.

The remainder of this paper is structured as follows. Section 2 presents previous related works. A description of the problem considered in this paper is provided in Section 3. The ILP formulation of the PFRSP is presented in Section 4. The exact-solving approach and the alternative heuristic one are detailed in Section 5. Section 6 presents the study case around CDG developed in this work, and results obtained on this one are analysed and discussed in Section 7. Finally, Section 8 concludes and establishes potential future works.

2. Literature Review

This study considers a tactical flight rescheduling at an airport, through passenger-oriented metrics, during ground transportation disturbances. Therefore, this work involves three topics vastly studied in the literature: tactical handling of airside operations, optimization of transportation systems through passenger-oriented metrics and disruption effects on an intermodal transportation network. The first topic has been mostly studied through optimization methods focusing on flight-oriented metrics. Most passenger-oriented methods have been led at the strategic level. The final topic has been studied through analytical studies, generally lacking in optimization methods to propose recovery solutions. A literature review associated with each subject is proposed below.

Tactical handling of airside operations

On the airport side, Pujet (1999) is one of the first to propose a virtual queuing system to shift waiting times at the runway threshold directly to the gate. This improved airport efficiency by reducing fuel consumption and, therefore, airport carbon footprint. Later, Bohme et al. (2007) study the integration of departure and arrival runway scheduling problems to improve the overall airport efficiency. Kjenstad et al. (2013) integrate arrival and departure runway scheduling problems with the surface management problem at Arlanda airport. Khadilkar and Balakrishnan (2015) extend the integration by also considering the management of the flights in the Terminal Manoeuvring Area (TMA), which is the airspace surrounding an airport, through dynamic programming. Ma et al. (2019) also propose an integrated approach to optimize airport operations from terminals to the TMA. They consider resource capacity constraints and air conflict resolution in the TMA using a simulated annealing to reschedule flights. Guimarans and Padrón (2022) use a simulation approach for airport ground resource scheduling. Their approach increases schedule robustness with aircraft turnaround mostly on time in all scenarios. Ma et al. (2021) propose two ILP models and a simulated annealing to optimize the departure runway scheduling at CDG while considering arrival runway crossing. Ahmadian and Salehipour (2022) present a matheuristics for the aircraft landing problem. This algorithm relies mainly on an iterative destruction of aircraft landing sub-sequences. Their approach enables to obtain optimal schedules for instances up to 50 aircraft and best-known solutions for instances up to 500 aircraft in less than a minute of computation time. Evler et al. (2021) highlight how an integrated decision support system for schedule recovery would help the Airport Operator Centre (AOC) for ground operation handling under uncertain arrival times. Through a study case around Frankfurt airport, they show the robustness of their solution with the consideration of 20 aircraft during a morning peak.

On the airline side, several works have been carried out regarding disruption management, including passenger recovery. Different approaches propose an integrated recovery that considers both aircraft re-routing and passengers (Jozefowicz et al., 2013; Hu et al., 2016). Delgado et al. (2016) combine two strategies for airlines to recover delays in a hub strategy. The first strategy relies on dynamic cost indexing, which allows aircraft to be accelerated to recover delays, while the other relies on delaying departing aircraft to wait for connecting passengers. Montlaur and Delgado (2017) optimize flight and passenger delay at tactical and pre-tactical levels. Optimization at the pre-tactical level succeeds in limiting propagated delays and in reducing the number of passengers missing their connections. Bouarfa et al. (2018) use a multi-agent system to propose a disruption management policy for an airport operations centre. Gurtner et al. (2021) propose an agent-based air traffic delay management model through 4D trajectory

adjustment in a European airport network. De La Vega et al. (2022) proposes to solve a short-term flight rescheduling problem to recover flight delays in the context where employees of a gas and oil company need to be transported to maritime units.

Transportation service optimization through passenger-oriented metric

Most passenger-oriented optimization works have been led with a clear distinction between air transport and ground transportation systems. Regarding the airport side, Dell’Orco et al. (2017) propose a fuzzy bee colony optimization to minimise the total passenger walking time by optimizing gate allocation to flights. Kim et al. (2017) optimize gate/flight allocation with a trade-off between the passenger transit time through the airport, the aircraft taxi time and the robustness of gate assignment. Birolini et al. (2023) proposes a change of paradigm for optimizing slot allocation through passenger-oriented metrics. Buire et al. (2022) propose a strategic synchronisation to coordinate train and flight timetables based on passenger transfer time at CDG airport. On the ground transportation level, Guajardo and Rönnqvist (2016) report over 40 cost allocation methods retained in collaborative transport. Their work can be seen as a baseline for implementing collaborative decision-making processes and achieve single ticketing. On the ground side, Rahimi Mazrae Shahi et al. (2016) optimize subway headways to minimise passenger travel time while having appropriate train load factors. They combine a discrete-event simulation and a response surface methodology to optimize the train schedule with limited simulation runs. Yu et al. (2021) study routing optimization in a multimodal context for passengers. They propose a mixed integer programming model and a heuristic to find optimal routing with a combined use of ride-sharing and public transport. They highlight that passengers using both combinations could reduce up to 7% and 8% the total vehicle travel distance and the vehicle travel time, respectively. Finally, Filippi et al. (2023) proposes a literature review on passenger transport optimization at an urban scale.

Effect of disruptions on a multimodal transportation network

Dray et al. (2015) and Marzuoli et al. (2015) analyse disruptive events on multimodal networks. Both highlight how multimodal recovery solutions should help in improving passenger-door-to-door journeys. Liu et al. (2021) present a review on public transportation coordination at the tactical level. Siegrist and Corman (2020) study the direct and indirect effects of a disruption in a public transport network. They highlight the impact of different information dissemination strategies in passenger delays through a simulation-based evaluation using MATSim tool (W Axhausen et al., 2016). They highlight that informing passengers about the disruption at the latest moment induces large passenger delays, mainly at the disrupted station. On the contrary, a beforehand dissemination induces more indirect effects spread over the entire network and a higher number of small delays for passengers indirectly affected by the disruption. Rothe et al. (2022) evaluate the impact of passenger delays and multimodal airport operations on two case studies. (Scozzaro et al., 2022b) propose a dynamic security team reallocation to mitigate airport facilities congestion when outbound passenger flow is disrupted. Scozzaro et al. (2022a) is the first to propose a dynamic flight rescheduling when an airport access mode disruption occurs. Assuming information sharing between ground and air transportation stakeholders, they propose a simulated annealing coupled with a simulation-based evaluation to reschedule flights and minimise the number of stranded passengers.

There is still a gap in the literature in studying how airports could react to access mode disruption. Here, we propose to enhance the work presented in Scozzaro et al. (2022a) through a linear reformulation

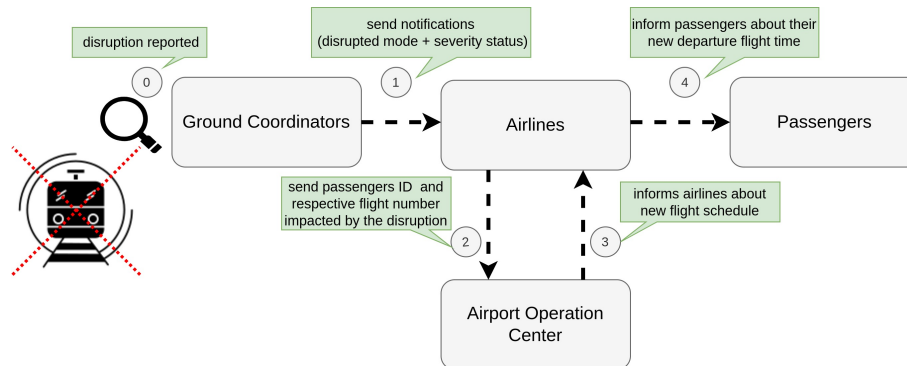


Fig. 1: Illustration of communication links between stakeholders

of the PFRSP, enabling an optimal solving approach.

3. Description of the Passenger-oriented Flight ReScheduling Problem (PFRSP)

This section presents the operational problem considered in this paper. First, the communication links between transportation stakeholders, which are required for this problem to reschedule flights at the tactical level, are described. Then, the optimization problem and the proposed airport modelling are detailed.

3.1. Communication links

When an airport access mode goes under disruptions, several passengers are likely to be delayed, and several may miss their flights. If the Airport Operation Centre (AOC) identifies these passengers early enough, their associated departure flights can be delayed to wait for them. Therefore, efficient communication links between transportation stakeholders are one key component to implementing such a coordination mechanism. The successive steps are illustrated in Fig. 1. We assume that the coordinator in charge of this mode reports the disruption and its severity level to airlines as soon as it is aware. Then, airlines can communicate to the AOC about passengers impacted by the disruption and their associated flights. The airport coordinator could estimate new aircraft filling rates and launch the flight rescheduling optimization tool based on this information. A new flight schedule is finally obtained and transmitted to airlines that can inform passengers of the new flight departure time.

3.2. Description of the considered optimization problem

We propose rescheduling flights to limit the impact of airport access mode disruptions on passenger door-to-door journeys. We assume that the AOC receives regular updates on passenger arrival time forecasts.

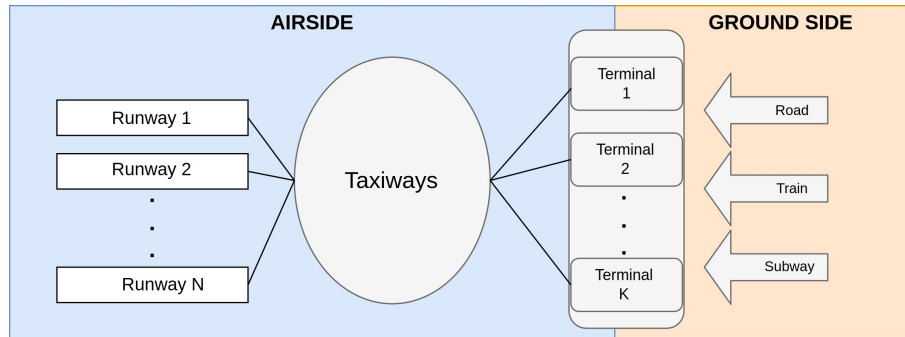


Fig. 2: Airport macroscopic model

Based on these forecasts, the AOC can identify flights that need to be delayed to reduce the number of passengers stranded at the airport. Since an airport has a limited capacity, delaying only departure flights may induce airport congestion. Thus, rescheduling both departure and arrival flight sets is considered to limit the impact of an access mode disruption while mitigating airport congestion. From an operational perspective, airport aircraft flow is managed by air traffic control tools that regulate flights according to demand and capacity. This process involves the Departure Manager (DMAN) and the Arrival Manager (AMAN) or its extended version, E-AMAN. DMAN allocates runways and departure delays based on runway pressure and slots allocated by the Network Manager. Similarly, AMAN/E-AMAN organises the sequence of arriving flights. As we propose rescheduling flights at the tactical level, i.e. a few hours before the operations, such a rescheduling tool should be interfaced with DMAN and AMAN/E-AMAN.

For this problem, a macroscopic view of the airport is retained, as illustrated in Fig.2. Passengers can access the airport through different ground transportation modes (e.g. road, subway, train). The airport is characterised by a set of terminals, a taxi network and a set of runways. Each element can be seen as a resource with a limited capacity. Each runway is either dedicated to arrival or departure flights. The taxi network links the different runways to the terminals. A departure flight leaves its stand (or gate), transits through the taxi network, reaches the runway threshold and finally takes off. Similarly, an arrival aircraft lands on a runway and transits through the taxi network to reach its gate. The gate departing and arriving times are called off-block time and in-block time, respectively. For simplicity, the taxiing time of a flight is assumed constant and only function of its associated terminal and runway. Moreover, the problem modelling does not consider queuing time at the runway threshold and, therefore, we assume an aircraft can take off as soon as it reaches the runway threshold.

Several decisions have to be made: A new off-block time and a new departure runway must be assigned to each departure flight. Similarly, a new landing time and a new arrival runway must be assigned to each arrival flight.

Three minimisation criteria are considered to make these decisions:

- the total number of stranded passengers,
- the total time deviation compared to the initial flight schedule,
- the total number of flights delayed by 15 minutes or more.

The last criterion relates to the On-Time Performance (OTP) metric that is widely used to measure airline

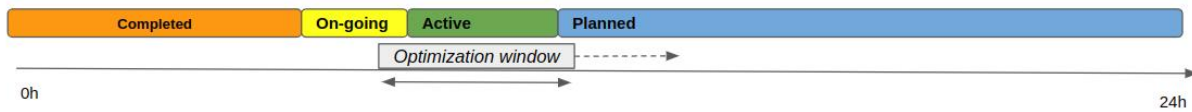


Fig. 3: Illustration of the different flight statuses for one optimization window.

punctuality (OAG, 2023). According to this criterion, a flight is considered delayed if its actual delay is equal to or greater than 15 minutes.

Three sets of constraints are considered: aircraft and flight-related, flight pair, and airport resource constraints. The first ones constrain the maximum delay that can be applied to each flight. Departures can only be delayed as it is rare for a flight to depart earlier than scheduled. However, an arriving flight can be accelerated in the air to arrive earlier. Therefore, we assume that arrivals can be slightly advanced or delayed. In addition, a priority status is given to departures that must be on time regarding the OTP metric, i.e. delayed by 10 minutes or less. In the following, the maximum assignable departure delay is set to 20 minutes, and arrival flight times can be deviated from -5 minutes up to +15 minutes. The second set of constraints imposes a minimum time between landing and departing times of several flight pairs. For instance, when an aircraft operates consecutively an arrival flight and a departure one, a minimum turnaround time constraint is considered. Similarly, a minimum transfer time is imposed between arrivals and departures that share connecting passengers. The last set of constraints is defined for each airport resource. Each terminal and the taxi network have a maximum capacity, translated into a maximum occupancy level. These capacities reflect limitations in the number of aircraft that can be handled by aircraft operators, such as air traffic controllers or ground handling teams, or due to physical resource limitations, e.g., the number of stands or taxiways. Since the number of airport operators is dynamic during the day of operations, a dynamic maximum capacity for each resource is considered. The capacity of each resource is set for each hour, and details on its computation are provided in Section 6. The taxi network is assumed to be a common resource shared by both departure and arriving flights. Each runway is also assumed to be constrained by a maximum throughput per time step. The problem of rescheduling is defined for a specific time window. In an operational context, the flight rescheduling tool would be launched when the access mode disruption occurs. It would be relaunched regularly during the day to reschedule the next flights when passenger arrival time forecasts would have been updated.

This work uses the methodology proposed by (Ma et al., 2019) that assigns a status to each flight for a specific optimization time window. Four statuses are considered (completed, on-going, active and planned). The first and second statuses refer to flights that have already been operated during the day, but the on-going ones can still occupy airport resources, e.g. a flight taxiing from its stand to the runway. Active flights are the ones for which decision variables are taken during the time window. The planned status concerns flights that will be operated after the time window. Fig. 3 illustrates the four statuses for a specific time window. On-going and planned flights can induce occupancy variation on airport resources. These flights are seen as a constraint for the problem instance associated with this specific time window. Finally, we only consider the scheduled departure or arrival time of flights and do not consider delays other than those assigned by the rescheduling algorithm, such as those related to air traffic flow management. The following section introduces the ILP model developed to solve the PFRSP over one time window.

4. Mathematical Modelling

Data, decision variables, constraints and the objective function are detailed below. Departure and arrival flights sets are defined for flights with the ‘active’ status. Non ‘active’ flights linked by a constraint to an active one are also considered. We define the following sets and parameters :

Sets and subsets :

\mathcal{D}	set of departing flights
\mathcal{A}	set of arriving flights
$\mathcal{F} = \mathcal{D} \cup \mathcal{A}$	set of flights
$\mathcal{D}^{\text{priority}} \subset \mathcal{D}$	set of departing flights that need to be on time regarding the OTP metric
\mathcal{K}	set of terminals
$\forall k \in \mathcal{K}, \mathcal{F}^k = \mathcal{D}^k \cup \mathcal{A}^k$	subset of departing and arriving flights associated to terminal k
\mathcal{R}^l	set of landing runways
\mathcal{R}^{to}	set of takeoff runways
$\mathcal{T} = \{t_{\text{start}}, t_{\text{start}} + \delta t, \dots, t_{\text{end}}\}$	set of discrete times on the time window considered (with δt the time step retained for the time discretisation, equals to 5 minutes in the following)
\mathcal{HT}	set of hours considered in \mathcal{T} (used to set hourly capacities of each resource)
$\mathcal{AD} = \mathcal{AD}^{\text{cog-a}} \cup \mathcal{AD}^{\text{a-a}} \cup \mathcal{AD}^{\text{a-p}}$	subset of arrival/departure pairs that are operated by the same aircraft. It is composed of three subsets depending on the status of each flight (completed/ongoing-active, active-active, active-planned)
$\mathcal{CF} = \mathcal{CF}^{\text{cog-a}} \cup \mathcal{CF}^{\text{a-a}} \cup \mathcal{CF}^{\text{a-p}}$	set of flight pairs having at least one connecting passenger (composed of three subsets: completed/ongoing-active, active-active, active-planned)
$\forall f \in \mathcal{A}, \mathcal{T}_A^f$	subset of time steps when f can land
$\forall f \in \mathcal{D}, \mathcal{T}_D^f$	subset of time steps when f can depart from its gate
$\forall t \in \mathcal{T}, \mathcal{A}^t = \{f \in \mathcal{A} \mid t \in \mathcal{T}_A^f\}$	subset of arriving flights that can land at time step t
$\forall t \in \mathcal{T}, \mathcal{D}^t = \{f \in \mathcal{D} \mid t \in \mathcal{T}_D^f\}$	subset of departing flights that can depart from the gate at t

Parameters :

$\forall f \in \mathcal{A}, T_f^{\text{l/in}}$	initial landing time/in-block time of flight f
$\forall f \in \mathcal{D}, T_f^{\text{out/to}}$	initial off-block time/takeoff time of flight f
$\forall f \in \mathcal{D}, T_f^{\text{to}}$	initial takeoff time of flight f
$\forall f \in \mathcal{F}, k_f$	terminal associated to f
$\forall k \in \mathcal{K}, \forall r \in \mathcal{R}^l, \delta t_{k,r}^{\text{in}}$	average taxi time from runway r to terminal k
$\forall k \in \mathcal{K}, \forall r \in \mathcal{R}^{\text{to}}, \delta t_{k,r}^{\text{out}}$	average taxi time from terminal k to runway r
$\forall (k_1, k_2) \in \mathcal{K}^2, \delta w_{k_1, k_2}$	minimum passenger transfer time from terminal k_1 to k_2
$\forall (f_1, f_2) \in \mathcal{AD}, \lambda_{f_1, f_2}$	minimum turnaround time for aircraft operating flights f_1 and f_2
$\forall t \in \mathcal{T}, h_t$	hour that t belongs to
$\forall k \in \mathcal{K}, N_k^{\text{init}}$	initial occupancy of terminal k at t_{start}
$\forall k \in \mathcal{K}, \forall h \in \mathcal{HT}, C_h^k$	maximum capacity of terminal k at h
$\forall r \in \mathcal{R}, \forall h \in \mathcal{HT}, \Phi_{r,h}^{\text{max}}$	maximum throughput of runway r on hour h
$\forall h \in \mathcal{HT}, C_h^{\text{TN}}$	maximum capacity of the taxi network at h
$\Delta t^{\text{l+/-}}$	maximum/minimum landing delay that can be applied to a flight (= -5minutes /+15minutes)
$\Delta t^{\text{out+}}$	maximum off-block time delay that can be applied to a flight (=20 minutes)
$\forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \Delta_{k,t}^{\text{OGP}}$	occupancy variation of terminal k at t due to on-going flights and planned flights
$\forall t \in \mathcal{T}, \Delta_{\text{TN},t}^{\text{OGP}}$	occupancy variation of taxi network at t due to on-going and planned flights
$\forall r \in \mathcal{R}, \forall t \in \mathcal{T}, \Delta_{r,t}^{\text{OGP}}$	number of on-going or planned flights on runway r at t
$\Delta t^{\text{on-time}}$	maximum takeoff deviation time without impacting the OTP metric
$\forall f \in \mathcal{D}, \forall t \in \mathcal{T}_D^f, g_{ft}$	number of stranded outbound passengers (i.e. non air-connecting passengers) if f departs from its gate at t

Sets \mathcal{T}_D^f and \mathcal{T}_A^f include constraints related to the maximum delay that can be assigned to a departure or an arrival flight f . Introducing such sets requires some data pre-processing but has the advantage of introducing fewer decision variables. As this time window problem does not involve any decisions on planned and on-going flights, they are considered as a constraint for the mathematical model. However, several flights with this status are partially operated during the considered time window. Consequently, such flights occupy airport resources (e.g. an on-going flight that is already taxiing at t_{start} will occupy the taxiing network at least at t_{start}). The parameters $\Delta_{k,t}^{OGP}$ and $\Delta_{r,t}^{OGP}$ sum the variation in occupancy due to planned and on-going flights for each airport resource and for each time step to update the actual airport resource occupancy.

The following main decision variables are introduced to reschedule flights:

$$\begin{aligned} \forall f \in \mathcal{A}, \forall t \in \mathcal{T}_A^f, \forall r \in \mathcal{R}^1, x_{f,t,r}^1 &= \begin{cases} 1 & \text{if flight } f \text{ lands on runway } r \text{ between } t \text{ and } t + \delta t \\ 0 & \text{otherwise} \end{cases} \\ \forall f \in \mathcal{D}, \forall t \in \mathcal{T}_D^f, \forall r \in \mathcal{R}^{to}, x_{f,t,r}^{out} &= \begin{cases} 1 & \text{if flight } f \text{ leaves the gate between } t \text{ and } t + \delta t \text{ and takes off on runway } r \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

We introduce the following auxiliary decision variables in order to properly formulate the constraints:

$$\begin{aligned} \forall k \in \mathcal{K}, \forall t \in \mathcal{T}, n_t^k & \text{ number of aircraft occupying terminal } k \text{ at } t \\ \forall t \in \mathcal{T}, n_t^{TN} & \text{ number of aircraft occupying taxi network at } t \\ \forall f \in \mathcal{A}, t_f^l & \text{ actual landing time of flight } f \\ \forall f \in \mathcal{A}, t_f^{in} & \text{ actual in-block time of flight } f \\ \forall f \in \mathcal{D}, t_f^{out} & \text{ actual off-block time of flight } f \\ \forall f \in \mathcal{D}, t_f^{to} & \text{ actual takeoff time of flight } f \\ \forall f \in \mathcal{D}, y_f &= \begin{cases} 1 & \text{if } t_f^{to} - T_f^{to} > \Delta t^{on-time} \text{ (delayed flight regarding OTP metric)} \\ 0 & \text{otherwise (on-time flight regarding OTP metric)} \end{cases} \end{aligned}$$

We formulate the following linear constraints:

$$\sum_{t \in \mathcal{T}_A^f} \sum_{r \in \mathcal{R}^1} x_{f,t,r}^1 = 1 \quad \forall f \in \mathcal{A} \quad (1)$$

$$\sum_{t \in \mathcal{T}_D^f} \sum_{r \in \mathcal{R}^{to}} x_{f,t,r}^{out} = 1 \quad \forall f \in \mathcal{D} \quad (2)$$

$$t_f^l = \sum_{t \in \mathcal{T}_A^f} \sum_{r \in \mathcal{R}^1} t \cdot x_{f,t,r}^1 \quad \forall f \in \mathcal{A} \quad (3)$$

$$t_f^{in} = \sum_{t \in \mathcal{T}_A^f} \sum_{r \in \mathcal{R}^1} (t + \delta t_{r,k_f}^{in}) \cdot x_{f,t,r}^1 \quad \forall f \in \mathcal{A} \quad (4)$$

$$t_f^{out} = \sum_{t \in \mathcal{T}_D^f} \sum_{r \in \mathcal{R}^{to}} t \cdot x_{f,t,r}^{out} \quad \forall f \in \mathcal{D} \quad (5)$$

$$t_f^{to} = \sum_{t \in \mathcal{T}_D^f} \sum_{r \in \mathcal{R}^{to}} (t + \delta t_{k_f,r}^{to}) \cdot x_{f,t,r}^{out} \quad \forall f \in \mathcal{D} \quad (6)$$

$$t_{f_2}^{\text{out}} - T_{f_1}^{\text{in}} \geq \lambda_{f_1, f_2}^{\min} \quad \forall (f_1, f_2) \in \mathcal{AD}^{\text{cog-a}} \quad (7)$$

$$t_{f_2}^{\text{out}} - t_{f_1}^{\text{in}} \geq \lambda_{f_1, f_2}^{\min} \quad \forall (f_1, f_2) \in \mathcal{AD}^{\text{a-a}} \quad (8)$$

$$T_{f_2}^{\text{out}} - t_{f_1}^{\text{in}} \geq \lambda_{f_1, f_2}^{\min} \quad \forall (f_1, f_2) \in \mathcal{AD}^{\text{a-p}} \quad (9)$$

$$t_{f_2}^{\text{out}} - T_{f_1}^{\text{in}} \geq \delta w_{k_{f_1}, k_{f_2}} \quad \forall (f_1, f_2) \in \mathcal{CF}^{\text{cog-a}} \quad (10)$$

$$t_{f_2}^{\text{out}} - t_{f_1}^{\text{in}} \geq \delta w_{k_{f_1}, k_{f_2}} \quad \forall (f_1, f_2) \in \mathcal{CF}^{\text{a-a}} \quad (11)$$

$$T_{f_2}^{\text{out}} - t_{f_1}^{\text{in}} \geq \delta w_{k_{f_1}, k_{f_2}} \quad \forall (f_1, f_2) \in \mathcal{CF}^{\text{a-p}} \quad (12)$$

$$y_f \geq \frac{t^{\text{to}} - T^{\text{to}} - \Delta t^{\text{on-time}}}{\Delta t_f^{\text{out+}} + \max_{r \in \mathcal{R}^{\text{out}}} \delta_{k_f, r}} \quad \forall f \in \mathcal{D} \quad (13)$$

$$y_f = 0 \quad \forall f \in \mathcal{D}^{\text{priority}} \quad (14)$$

$$n_{t_{\text{start}}}^k = N_k^{\text{init}} + \Delta_{k, t_{\text{start}}}^{\text{OGP}} \quad \forall k \in \mathcal{K} \quad (15)$$

$$n_{t+\delta t}^k = n_t^k + \sum_{r \in \mathcal{R}^1} \sum_{f \in \mathcal{A}^k \cap \mathcal{A}^{t'}} x_{f, t', r}^1 - \sum_{r \in \mathcal{R}^{\text{to}}} \sum_{f \in \mathcal{D}^k \cap \mathcal{D}^t} x_{f, t, r}^{\text{out}} + \Delta_{k, t+\delta t}^{\text{OGP}},$$

where $t' = t - \delta t_{k_f, r}^{\text{out}}$

$$\forall k \in \mathcal{K}, \forall t \in \mathcal{T} \setminus t_{\text{end}} \quad (16)$$

$$n_t^k \leq C_{h_t}^k \quad \forall t \in \mathcal{T}, \forall k \in \mathcal{K} \quad (17)$$

$$n_{t_{\text{start}}}^{\text{TN}} = \Delta_{\text{TN}, t_{\text{start}}}^{\text{OGP}} \quad \forall k \in \mathcal{K} \quad (18)$$

$$n_{t+\delta t}^{\text{TN}} = n_t^{\text{TN}} + \sum_{r \in \mathcal{R}^1} \left(\sum_{f \in \mathcal{A}^t} x_{f, t, r}^1 - \sum_{k \in \mathcal{K}} \sum_{f \in \mathcal{A}^{t'} \cap \mathcal{A}^k} x_{f, t', r}^1 \right) +$$

$$\sum_{r \in \mathcal{R}^{\text{to}}} \left(\sum_{f \in \mathcal{D}^t} x_{f, t, r}^{\text{out}} - \sum_{f \in \mathcal{D}^{t''}} x_{f, t'', r}^{\text{out}} \right) + \Delta_{\text{TN}, t+\delta t}^{\text{OGP}},$$

where $t' = t - \delta t_{r, k_f}^{\text{in}}$ and $t'' = t - \delta t_{k_f, r}^{\text{out}}$

$$\forall t \in \mathcal{T} \setminus t_{\text{end}} \quad (19)$$

$$n_t^{\text{TN}} \leq C_{h_t}^{\text{TN}} \quad \forall t \in \mathcal{T} \quad (20)$$

$$\sum_{r \in \mathcal{R}^1} \sum_{f \in \mathcal{A}^t} x_{f, t, r}^1 + \Delta_{r, t}^{\text{OGP}} \leq \phi_{r, h_t}^{\max} \quad \forall r \in \mathcal{R}^1, \forall t \in \mathcal{T} \quad (21)$$

$$\sum_{r \in \mathcal{R}^{\text{to}}} \sum_{f \in \mathcal{D}^{t'}} x_{f,t',r}^{\text{out}} + \Delta_{r,t}^{\text{OGP}} \leq \phi_{r,h_t}^{\text{max}}, \quad \text{where } t' = t - \delta_{k_f,r}^{\text{out}}, \quad \forall r \in \mathcal{R}^{\text{to}}, \forall t \in \mathcal{T} \quad (22)$$

$$x_{f,t,r}^1 \in \{0, 1\} \quad \forall f \in \mathcal{A}, \forall t \in \mathcal{T}_{\mathcal{A}}^f, \forall r \in \mathcal{R}^1 \quad (23)$$

$$x_{f,t,r}^{\text{out}} \in \{0, 1\} \quad \forall f \in \mathcal{D}, \forall t \in \mathcal{T}_{\mathcal{D}}^f, \forall r \in \mathcal{R}^{\text{to}} \quad (24)$$

$$y_f \in \{0, 1\} \quad \forall f \in \mathcal{D} \quad (25)$$

Constraint (1) (resp. (2)) refers to arrival (resp. departure) time and runway assignment constraint. Landing time, in-block time, off-block time and takeoff time intermediate variables are fixed thanks to constraints (3), (4), (5) and (6) respectively. Constraints (7), (8), (9) impose minimum turnaround time for flights operated by the same aircraft. Each one depends on the flight status of the pair considered. Similarly, constraints (10), (11), (12) translate minimum transfer time for flights having at least one connecting passenger. Constraint (13) fixes the value of the binary variable y_f that determines if a flight f is delayed regarding the OTP metric. Constraint (14) forces priority flights to be delayed by 10 minutes or less. Constraint (15) fixes the initial terminal occupancy. Constraint (16) fixes the next occupancy of each terminal depending on the current one at time t . It is equal to the current occupancy plus flights arriving at the block at t minus the ones departing from the block at t and an occupancy variation term due to on-going or planned flights. Terminal capacity constraints are represented through (17). Analogous constraints are applied for the taxi network through (18), (19) and (20). Finally, throughput constraints related to arrival and departure runways are represented by (21) and (22) respectively.

A multi-criteria function is considered and several terms need to be introduced:

- G that represents the total number of stranded outbound passengers:

$$G = \sum_{f \in \mathcal{D}} \sum_{t \in \mathcal{T}_{\mathcal{D}}^f} \sum_{r \in \mathcal{R}^{\text{to}}} g_{f,t} \cdot x_{f,t,r}^{\text{out}} \quad (26)$$

- D that quantifies the total in-block time and take-off time deviation from the initial schedule:

$$D = \sum_{f \in \mathcal{A}} |t_f^{\text{in}} - T_f^{\text{in}}| + \sum_{f \in \mathcal{D}} |t_f^{\text{to}} - T_f^{\text{to}}| \quad (27)$$

- Y that is a measure of the total number of delayed flights regarding OTP metric:

$$Y = \sum_{f \in \mathcal{D}} y_f \quad (28)$$

The objective function is the following one:

$$\min G + \alpha \cdot D + \beta \cdot Y, \quad \text{with } \alpha, \beta \geq 0. \quad (29)$$

α and β are parameters that can be adjusted by the airport operators depending on whether the rescheduling should favour a reduction in the total number of passengers missing their flights, the total deviation time from the schedule or the number of flights delayed by 15 minutes or more. For example, for $(\alpha, \beta) = (0.1, 1)$, a 20-minute flight delay has the same impact on the objective function as three passengers missing their flight.

The objective function is not linear at this stage due to the absolute values. However, it can easily be linearised by adding an intermediate variable for each flight and constraining them to be higher than the schedule's positive and negative deviation.

The choice to consider absolute values for the total deviation time criterion is questionable. It might have been preferred to consider a quadratic term, which exact solvers can also handle through quadratic programming. However, such a penalty tends to favour an equitable solution, i.e. where each flight is affected by a small deviation. Such a solution would cause more work for air traffic controllers. On the other hand, the number of delayed flights could have been considered to favour parsimonious solutions. However, this could lead to larger delays and an increase in the number of flights delayed regarding the OTP metric. The absolute deviation seems to be a good compromise between creating parsimonious solutions and limiting the assignment of large delays.

5. Solving approach

First, two approaches for solving the ILP model on a specific time window are presented. Then, a sliding time window framework is proposed to allow online rescheduling of the flights from the beginning of the disruption up to the end.

5.1. Solving approach on one time window

The ILP model proposed in Section 4 can be optimally solved thanks to a commercial solver in main cases (see Section 7). In order to tackle the largest instances in a short computing time, as well as to compare the model results to solutions that could be ‘manually’ designed by an airport operator, we also propose a simple greedy heuristic to solve the PFRSP.

The main idea of this algorithm is to reduce the number of stranded passengers by delaying in priority flights that have the highest impact on this criterion. Therefore, the following score s for each couple of flight and delay (f, d) is computed:

$$s(f, d) = \frac{p_{f,d}}{1 + \epsilon \cdot d} \quad (30)$$

where $p_{f,d}$ corresponds to the number of ‘saved’ passengers if the flight f is delayed by a delay d and ϵ a positive parameter. Here, the higher the score is, the more efficient the couple (f, d) is. If $\epsilon \ll 1$, a lexicographical order is used to rank score first by the number of ‘saved’ passengers and, in case of equality, by the smaller deviation from the initial schedule. Conversely, if ϵ is set to a high value, small delays are prioritised. For the sake of simplicity, the runway decision for departure and arrival flights is

not changed with this heuristic. Fig. 4 displays a flow chart representing the main steps of this heuristic.

In order to focus only on (flight, delay) pairs that are relevant, a pre-processing step is carried out. For instance, delays over 10 minutes are not tested with priority flights. These couples are ordered by decreasing score values and stored in a stack S . Then, the first couple (f, d) of S is unstacked, and the delay d is tested on flight f . If the maximum runway throughput is exceeded, the next element of S is unstacked. Otherwise, the terminal capacity constraint is evaluated. If an overload is observed, a recovery mechanism is launched to test if an arrival flight can be delayed to mitigate terminal congestion. Finally, the taxi capacity constraint is checked. If this one is satisfied, the departure flight's off-block time is updated and, if necessary, the flight's arrival time that mitigates terminal congestion is also updated. These flights are removed from consideration (i.e., all couples (f, d) including flight f from S are removed and the arrival flight is removed from the ones considered to alleviate airport congestion), and the next element of S is unstacked until this one is empty.

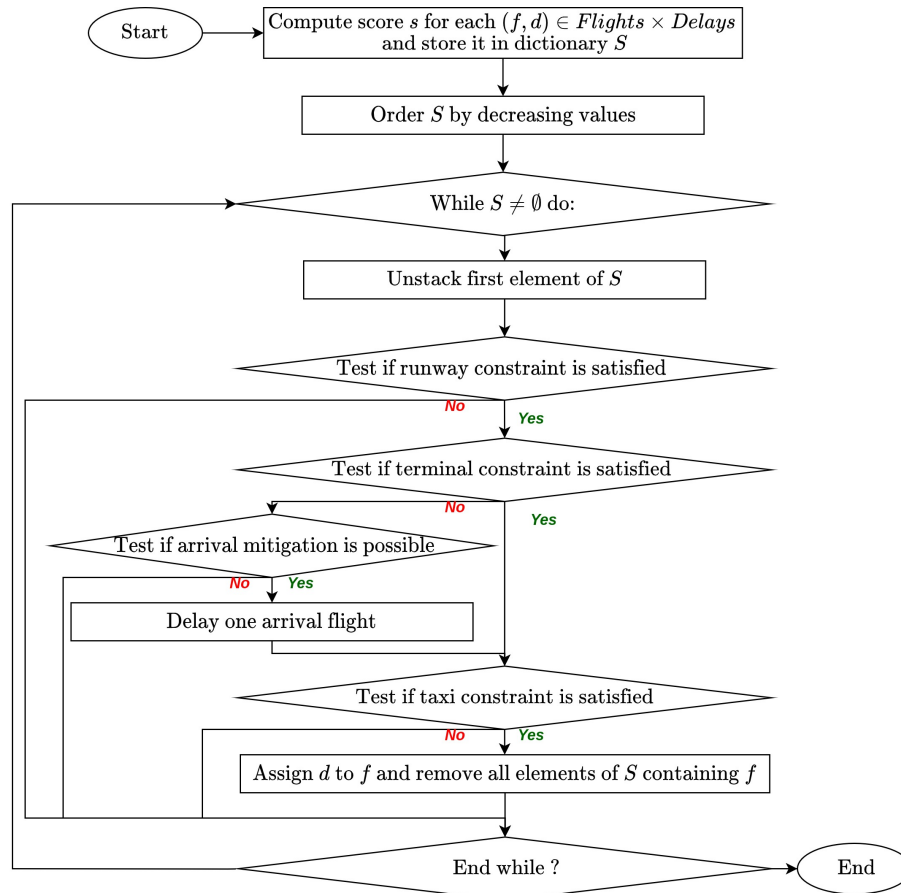


Fig. 4: Flow chart of the proposed heuristic

5.2. Online resolution approach

The flight rescheduling mechanism proposed in this paper aims at handling disruptive events, i.e. situations where actual passengers' arrival times are different from the forecast one. Information provided by airlines and ground operators would help to update these forecasts, but only for a limited time horizon. For instance, when an access mode disruption starts in the morning, forecasts related to passengers arriving in the evening are unreliable. Thus, rescheduling flights on a single time window lasting from morning to day's end is irrelevant. That's why a sliding time window approach is proposed to reschedule flights over the day. We assume the airport operation centre would receive regular updates on passenger arrival times. In the following, this update is assumed to be done every 30 minutes. Departure and arrival flights planned over the next hours following the new update could be rescheduled. We propose to reschedule flights expected between one and three hours after the moment of the rescheduling decision. The selection of these boundary values is motivated by the following considerations:

- Decisions on departure and arrival flights should be taken sufficiently early to inform air traffic controllers, pilots and other operators about the new schedule and avoid poor operation handling. Indeed, if a delay is communicated to an arrival flight ten minutes before its initial landing time, the flight would probably use a holding pattern. Such an operation should be avoided since it increases the fuel burn during the cruise. Conversely, if the delay is communicated between one to three hours in advance, speed regulation during the cruise phase or delay directly at the gate of the departure airport would be considered, limiting the extra-fuel consumption of the aircraft.
- The upper boundary is set regarding the reliability of passenger arrival time forecast. Consider an airport access mode disruption happening at t_{start} . Since CDG advises passengers to arrive two and three hours before short-haul and long-haul flights respectively (Paris Aéroport (2022)), first passengers affected by the ground disruption would have their flight planned between $t_{\text{start}} + 120\text{min}$ and $t_{\text{start}} + 180\text{min}$. Therefore, we assume passenger arrival time forecasts are reliable up to three hours.

Algorithm 1 describes the proposed sliding time window process. The rescheduling mechanism is launched for the first time at t_{start} to solve the PFRSP on $[t_{\text{start}} + 60\text{min}, t_{\text{start}} + 180\text{min}]$. Then, the PFRSP is solved again on the next time window shifted by 30 minutes. This process is repeated until the end of the disruption plus, eventually, extra time to recover the initial schedule due to the domino effect.

Algorithm 1 SlidingTimeWindowManagement($tMin, tMax, x$)

$tStart = tMin$

$tEnd = tMin + \Delta TW$

repeat

$x \leftarrow \text{reschedulingFlights}(x, tStart, tEnd)$

$tStart = tStart + \delta TS$

$tEnd = tEnd + \delta TS$

until $tStart + \delta TS \geq tMax$

In this algorithm, x represents the decision variable vector, $tMin$ and $tMax$ the starting and ending time of the rescheduling, ΔTW the time window duration, δTS the time window shift and $\text{reschedulingFlights}()$ the algorithm used to solve the PFRSP.

6. Study case description

In the following, a study case around Paris-Charles de Gaulle airport is presented. First, a description of airport characteristics and the methodology retained to estimate resource capacities are described. Then, the passenger arrival modelling process is detailed. Finally, the different disruptive scenarios considered to generate instances of the PFRSP are presented.

6.1. General airport characteristics

A scheme of CDG airport is provided in Fig. 5. This airport comprises three main terminals (T1, T2, T3). Terminal T2 can be divided into seven terminals with two main ones (T2E and T2F) and five others (T2A, T2B, T2C, T2D, T2G). CDG airport has two pairs of parallel runways. Runways 27R and 26L are dedicated to arrival flights (externals runways in Fig. 5), whereas 27L and 26R are dedicated to departure flights.

This work uses historical flight schedules on CDG in June 2019. For each departure (respect. arrival) flight, the date, the initial and actual off-block times (respect. in-block times), the callsign, the terminal, the boarding room, the tail number, the destination (respect. origin) airport, the departure (respect. arrival) runway, the take-off (respect. landing) time and the number of carried passengers are known. Average taxi times for each couple (terminal, runway) can be computed thanks to this data set. These values are available in (Scozzaro, 2023).

We did not have access to information on resource capacity or the number of operators during the day. Therefore, we used the maximum expected occupancy per hour, computed through the initial schedule, as an estimator of the capacity of each terminal and the taxi network. We followed the same principle to infer the maximum throughput per time step for each runway. For each time step t , the maximum

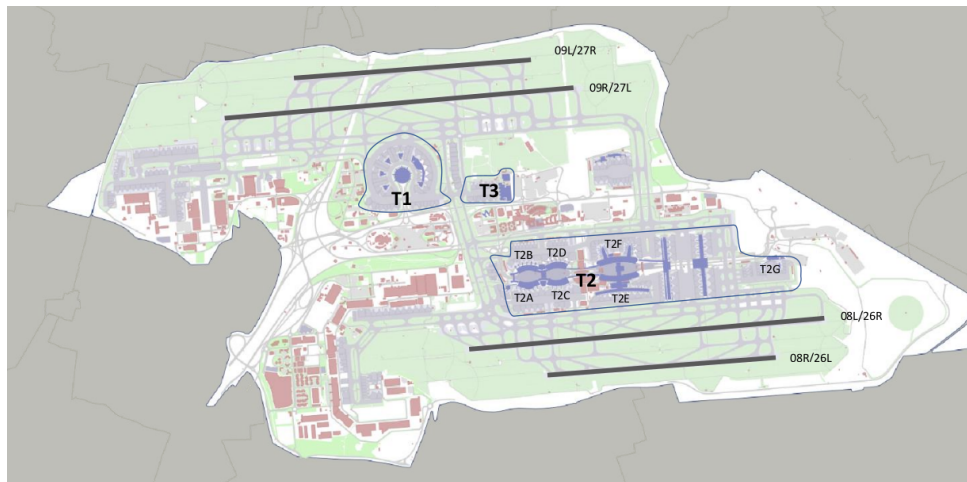


Fig. 5: CDG configuration overview

throughput is set to the maximum one initially observed within the hour that includes t .

6.2. Passenger modelling

In order to evaluate the relevance of the flight rescheduling process, a methodology to estimate the number of passengers missing their flights is required. Thus, one main challenge of this work is to model the passenger arrival process up to their boarding gate. We propose a data-driven approach to design realistic passenger arrival flows. First, the methodology retained to simulate connecting passengers is described. Then, the distribution fitting to design the nominal arrival process is presented. Finally, the modelling of the ground transportation disruption impact on passengers is presented.

6.2.1. Modelling connecting passengers

Information on connecting passengers is the property of the airlines and is generally not even known by the airport operators. Therefore, a methodology is proposed to generate connecting passengers. We used the flight schedule dataset and different statistics provided by CDG to model air passenger transfers. These statistics inform on the share of connecting passengers per departure terminal, minimum walking/transfer times between terminals and the proportion of connecting passengers between terminals. They are available through the reference (Scozzaro, 2023). Thanks to this information, the methodology presented by Scozzaro et al. (2022a) has been improved by taking into account the origin and destination airport, the connecting passenger share for departing flights depending on their associated terminals, the connecting passenger share between terminals and the minimum passenger transfer time between terminals. Only a subset of relevant flight pairs are considered to simulate connecting passengers. For example, only arrivals with a French-origin airport have been connected to international flights and vice versa, in order to reproduce the generic connecting scheme at hub airports. Considering a pair of arrival and departure flights (f_a, f_d) , we assume that they can have connecting passengers if the difference between the scheduled off-block time of f_d and the scheduled in-block time of f_a is greater than a Minimum Connecting Time (MCT) and less than a Maximum Acceptable Connecting Time (MACT). We arbitrarily set $\text{MACT} = \text{MCT} + 2\text{h}$. The MCT depends on the minimum transfer time between the terminals associated with flights f_a and f_d .

6.2.2. Modelling outbound passengers

We propose a data-driven approach to simulate the passenger arrival process at the airport. Three months of data related to passenger timestamps at the security screening system have been provided by CDG. This data set gives for each 10-minute interval, and for each flight, the number of passengers who went through the security screening system during this period. It can be combined with the flight schedule data set to infer how long passengers arrive before their departure flight.

Buire et al. (2021) show that an Exponentially Modified Gaussian (EMG) distribution can be fitted with the passenger timestamp data set to simulate passenger arrival flow at the airport for a given flight schedule and an expected number of passengers per flight. For subway and road access, continuous distributions such as the EMG one seem suitable to model passenger arrivals regarding the high frequency of passenger arrivals. However, regarding train access, passenger arrivals are scattered due to low train

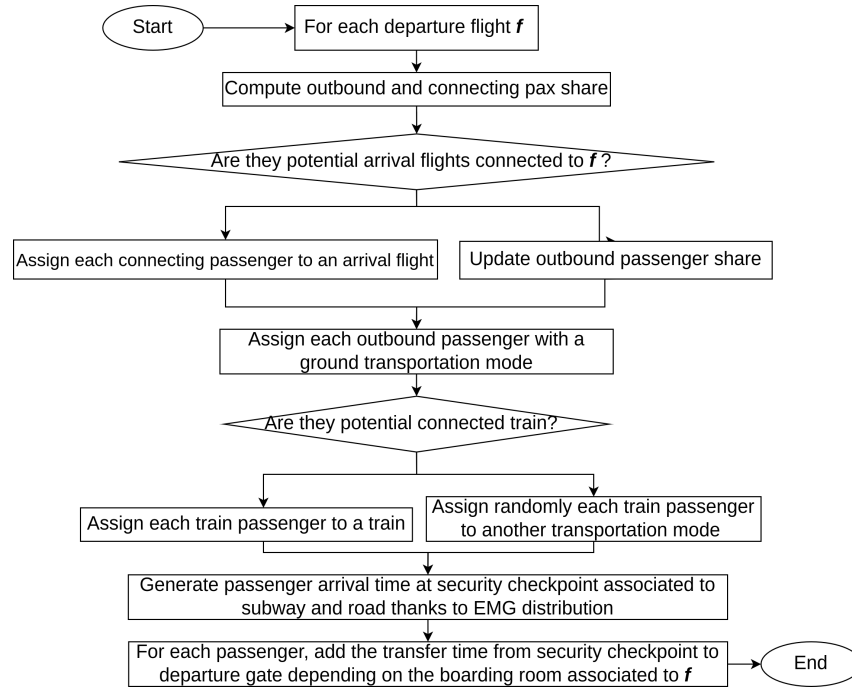


Fig. 6: Passenger arrival modelling flowchart

frequency. For this mode, GTFS data related to high-speed rail schedules have been collected for one typical day in 2019. Such data are regularly updated and available on SNCF website (SNCF, 2019). Each passenger associated to this mode is randomly assigned to a train arriving between 240 minutes and 90 minutes before the departure flight time. These values have been arbitrarily selected to provide enough transfer time for passengers. If no train is arriving during this time interval, passengers are randomly assigned to another transport mode. Since the actual access mode used by passengers in the passenger timestamp data set is unavailable, we randomly assign each passenger with a mode according to modal shares provided by DGAC, the French Civil Aviation Authority. They are equal to 11%, 26% and 63% for train, subway and road respectively. Thanks to the flight schedule data set, we know the actual number of passengers carried per aircraft.

Finally, CDG provided information on the average transit time from security checkpoints to the gate for each boarding room, available in (Scozzaro, 2023). Then, the passenger arrival time at the gate is computed by adding this transit time to the simulated arrival time at security checkpoints. Fig. 6. summarises the global procedure to model nominal passenger arrival at the boarding gate for one day.

6.2.3. Modelling the disruption

The passenger timestamp file does not provide information on whether or not passengers experienced a disruption on the mode they used to access the airport. Therefore, a methodology is needed to simulate passenger delays related to an airport access mode disruption. In the following, the methodology pro-

Table 1 Characteristics of the different disruptive scenarios

Scenario	Disrupted mode	Disruption starting time	Disruption ending time	Start passenger delay
S45	subway	7am	3pm	45min
R45	road	7am	3pm	45min
T45	train	7am	3pm	45min
S90	subway	7am	3pm	90min
R90	road	7am	3pm	90min
T90	train	7am	3pm	90min
S45_1	subway	5am	10am	45min
S45_2	subway	2pm	9pm	45min
S45_3	subway	5am	9pm	45min

posed by Scozzaro et al. (2022b) is applied. A ground transport mode is chosen, and it is assumed that it suffers a disruption between a start time t_{start} and an end time t_{end} . Passengers relying on this mode to get to the airport during the disruption are delayed. A distinction is made between high-frequency access modes (e.g. subway and road access) and low-frequency access modes (e.g. train access).

To model the impact of a subway or a road access mode disruption, a delay is assigned to passengers who are assumed to use the disrupted mode between t_{start} and t_{end} . A start delay is assigned at t_{start} to passengers, and this delay decreases linearly to 0 until t_{end} . This delay, which decreases linearly over time, models the passengers' responsiveness to disruptions as time progresses. For example, passengers have the option to choose a different route or allow extra time to arrive at the airport on time if they are made aware of any disruptions. Indeed, according to Paulsen et al. (2021), the more information a passenger receives about the disruption and the traffic situation, the more he can improve his routing decisions and reduce his delay. Leng and Corman (2020) also show through different simulated scenarios that for unexpected disruptions, higher passenger delays are observed at the beginning of a mode disruption.

Passengers who rely on trains to get to the airport tend to live far from the centre of Paris and therefore have fewer options for re-routing in the event of train disruption. In this case, if a train experiences a delay, passengers relying on that train are likely to experience a delay equal to the train delay. Therefore, we propose to model train disruptions through constant delays for passengers.

6.3. Test scenarios

Tests have been conducted on a historical day of operations. This day was the busiest day of June 2019 with 717 departure flights, carrying over 123 000 passengers. The scheduled departure and arrival times are taken into account, and for this study, we do not take into account actual flight delays. The methodology used to model passengers leads to the generation of 38 000 connecting passengers among the 123 000 departing ones.

Different disruptive scenarios are considered to test the rescheduling approach. Characteristics related to the different scenarios are presented in Table 1. Each scenario name is composed of the first letter of the disrupted mode (S, T, R for Subway, Train and Road, respectively) and the maximum delay experienced by passengers in minutes. Therefore, S45 simulates a subway disruption with passengers

experiencing a start delay equal to 45 minutes and decreasing linearly to 0 minutes at the end of the disruption. T45 simulates a train disruption with a constant passenger delay set to 45 minutes. These scenarios are designed to study the influence of the disruption severity and of the airport access mode in the flight rescheduling performance. The first six scenarios simulate a disruption lasting from 7am to 3pm. These times have been selected to consider a disruption happening during airport movement peaks (that are located at 9am and 12pm). The severity of the disruption will be analysed by comparing 45-minute and 90-minute delay scenarios, respectively. Finally, the last three scenarios are designed to test the influence of the starting and the ending disruption times on the rescheduling.

All the different instances related to each scenario are publicly available through reference (Scozzaro, 2023). For sensitivity issues, data related to airlines, delay and tail number have been removed and a noise has been added to the actual number of carried passengers per flight.

7. Results

This section presents tests and analyses conducted on the CDG study case. First, the different approaches for problem-solving are compared, and model parameter sensitivity is analysed on a single time window. Then, the performance of the online rescheduling approach on the different disruptive scenarios is discussed. Exact and heuristic algorithms have been tested on a Ryzen AMD5 4500U with Radeon GPU and 16GB. The Gurobi 9.5.0 solver is used to solve the ILP model proposed in Section 4. The maximum off-block time (OBT) delay is set to 20 minutes, while the arrival delay is limited between -5 and +15 minutes. A 5-minute time step is used, meaning the OBT delay can equal 0, 5, 10, 15 or 20 minutes.

7.1. Results on one time window

First, the optimal ILP model solving and the heuristic approach are compared. Then, the ILP performance is analysed depending on the time window duration and maximum OBT delay. The following tests are carried out on the S45 scenario, which models a disruption on the subway with passengers delayed up to 45 minutes.

7.1.1. Heuristic vs optimal ILP solving

For this study, the time window length is set to four hours. Since the objective function of the ILP model is multi-criteria, several couples (α, β) are tested to whether priorities one criterion or another. Similarly, the value of the score parameter ϵ used in the heuristic impacts the final solution. Fig. 7 presents criteria values obtained with the ILP model depending on weight parameters (α, β) . The lowest value obtained through the heuristic on each criterion is also displayed in red. Results related to the heuristic problem-solving approach in the function of ϵ are provided in Table 2.

The initial number of stranded passengers is equal to 249. The ILP-solving approach reduces this number to 92 for $(\alpha, \beta) = (0.1, 0)$, representing a 63% decrease in this criterion. This is 7% better than the best solution found by the heuristic. However, for this couple, the heuristic can perform better for the delay deviation and the OTP metric. The more the schedule deviation penalty increases, i.e. the higher α and β , the lower the reduction in the number of stranded passengers after optimal ILP rescheduling. If the

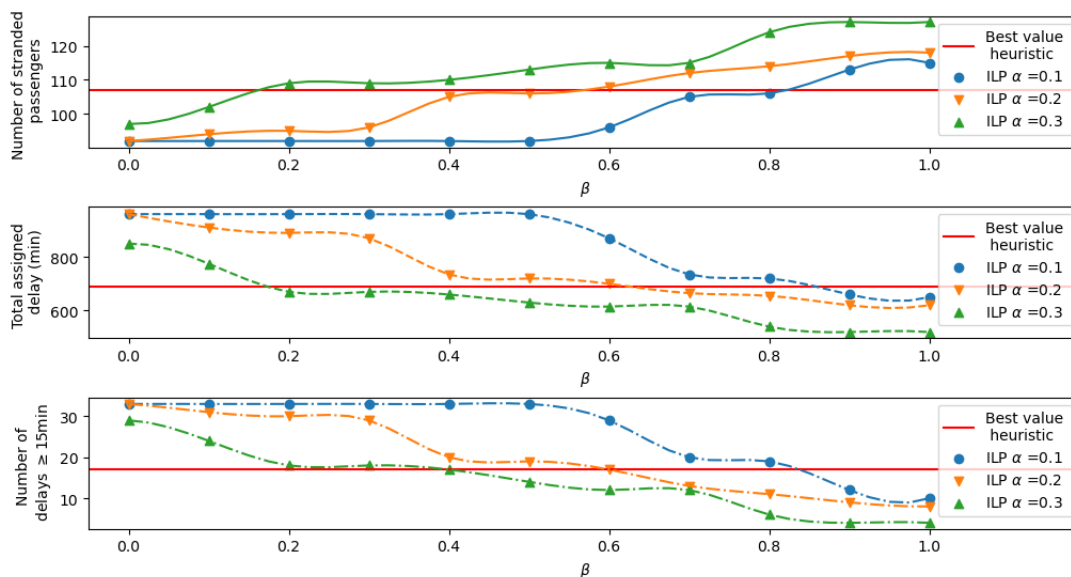


Fig. 7: Values of different criteria obtained after optimal ILP model solving on a 4-hour time window. Each graph corresponds to a criterion, and each point to one couple of weight parameters (α, β) . α is associated with the total flight delay criterion, while β is associated with the number of flights delayed by 15 minutes or more criterion. The larger these parameters, the less the algorithm assigns flight delays. The red lines correspond to the best value obtained with the heuristic approach for each criterion among the set of ϵ parameters tested.

Table 2 Criteria values after rescheduling with the heuristic approach depending on the score parameter ϵ (see Equation 30). This parameter penalises the score of a decision ‘Assign delay d to flight f ’ as a function of the delay d . A high ϵ will reduce the score of decisions, implying large flight delays. The best values are highlighted in bold.

ϵ	10^{-3}	10^{-2}	10^{-1}	1	10^1	10^2	10^3
stranded passengers	113	107	107	122	125	141	158
total deviation (min)	895	990	990	870	875	785	690
Number of delays ≥ 15 min	33	37	37	26	24	24	17

penalty overcomes a threshold, the exact ILP-solving approach provides a schedule with more stranded passengers than the heuristic approach. However, in parallel, a significant reduction in both other criteria is observed, and the exact solving outperforms the heuristic approach on both criteria. Comparing Fig. 7 and Table 2, when a similar value is obtained on one criterion with the heuristic and the ILP solving, the ILP one outperforms the heuristic one on the two other criteria. The heuristic can be efficient on one criterion but tends to degrade the two other ones. A trade-off between criteria can be found through ILP solution for couples $(\alpha, \beta) = (0.3, 0, 3)$, or $(0.2, 0, 6)$ for instance where the exact solution is almost as good as each best criterion value found by the heuristic depending on ϵ .

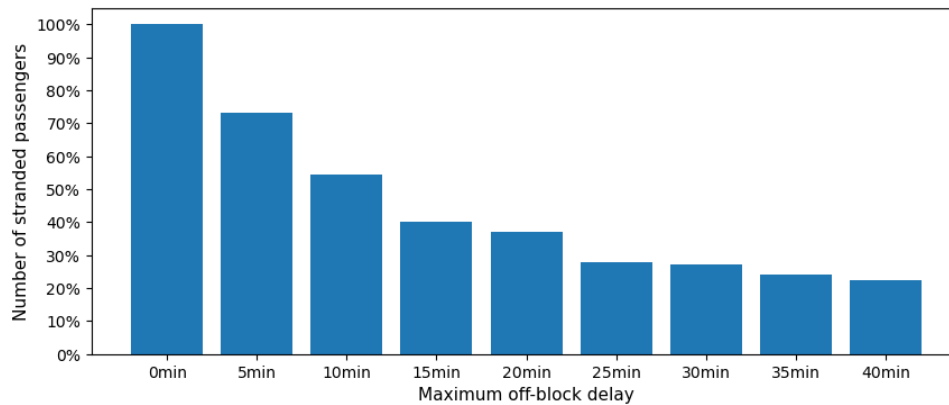


Fig. 8: Evolution of the relative number of stranded passengers as a function of the maximum off-block delay allowed. The relative number of stranded passengers is computed by comparing the number of stranded passengers before and after flight rescheduling.

Table 2 shows test results for $0.001 \leq \epsilon \leq 10000$. Note that the solution no longer varies for epsilon lower than 0.0001 or higher than 10000. Interestingly, the highest reduction in the number of stranded passengers is not obtained with the lowest ϵ . A closer look at solutions obtained with $\epsilon = 10^{-3}$ and $\epsilon = 10^{-2}$ lets us see that fewer flights are delayed for the smaller parameter value. This observation can be explained since reducing the deviation penalty tends to increase the score related to large delays. However, an aircraft experiencing a significant delay uses airport resources longer and could limit delay assignment for the next flights. Therefore, prioritising larger delays that save the highest number of passengers can lead to sub-optimal solutions regarding this criterion.

Finally, the average computation time of ILP and heuristic approaches are 0.6s and 0.02s, respectively. Therefore, the heuristic approach is 30 times faster than the exact ILP solving. However, the computation time of the exact solving is still acceptable for tactical airport operations handling. The impact of the time window duration on the ILP computation time has also been investigated. The computation time increases when the time window is lengthened since more flights are considered and, thus, more decision variables are generated. It goes from 0.1s up to 1.74s for a 2-hour and a 12-hour time window duration, respectively. Therefore, the optimal ILP solving is still efficient to reschedule flights planned over an entire day of operations. For the rest of the section, the presented results are obtained with the optimal ILP model solving.

7.1.2. Maximum off-block time delay sensitivity analysis

The impact of the maximum allowed OBT delay on the number of stranded passengers is investigated below. In other words, we conduct tests to measure if authorising larger delays would help reducing the number of stranded passengers. To evaluate this effect, the schedule deviation penalty is removed by setting (α, β) to $(0,0)$. Fig. 8 displays the obtained results.

As expected, the number of stranded passengers decreases when the maximum allowed pushback time increases. The decrease goes from 25% if the maximum delay is set to 5 minutes and steadily increases

up to 78%. Maximum OBT delays over 25 minutes induce smaller benefits due to resource capacity constraints. Indeed, when an aircraft is delayed, it uses a resource with a longer duration and, thus, is likely to induce congestion. Therefore, even for the solving with a maximum OBT delay set to 40 minutes, the average departure delay is lower than 18 minutes. Consequently, even after rescheduling flights while authorising large OBT delays, almost 20% of passengers who initially miss their flights remain stranded. This information could be provided to airlines to anticipate the need to reallocate these passengers on next flights. Finally, increasing the maximum delay widens the search space and thus can lengthen the computational time. This one is around 0.35s for a 5-minute maximum OBT delay and increases up to 0.82s for a 40-minute one.

7.2. Online resolution approach

Results obtained with the online resolution approach are presented below. As a reminder, this approach relies in solving sequentially ILP models on 2-hour time windows from the beginning of the disruption until the end of operations. It has been designed to handle data reliability related to passenger arrival time, which is limited in time during disruption. First, general results obtained for scenario S45 are presented. Then, the rescheduling obtained on the scenarios described in Table 1 are compared. A brief analysis is then carried out to examine the relevance of delaying arriving flights to reduce airport congestion. Finally, the impact of such flight rescheduling on air connecting passengers is analysed.

7.2.1. General results on scenario S45

Fig. 9 displays the evolution in the number of stranded passengers before and after rescheduling and the average aircraft delay assigned in scenario S45. One can observe that the number of stranded passengers is divided by two thanks to the rescheduling. A 2.5-minute and a 0.2-minute average delay are assigned to departure and arrival flights, respectively. By comparison, the actual average delay experienced by departing and arriving flights on this day of operations is equal to 20.5 minutes and 8.0 minutes respectively. The average arrival delay is lower than the departure one since arrival delays are only assigned to mitigate airport congestion. Since arrival delays can be equal to -5, 0, 5, 10, or 15 minutes, an average delay of 0.2 minutes means that a small proportion of flights are delayed. Fig. 10 shows the number of delayed flights as a function of the assigned delay, with a distinction between departures and arrivals. Most arrivals are on time, and only a few flights are delayed up to 15 minutes. For departures, 62% of flights meet their original OBT, and most of the delays attributed are less than 15 minutes. In this case, the flight rescheduling would have little impact on airlines' on-time performance, with 7% of rescheduled flights considered as delayed. By comparison, the actual percentage of flights delayed by 15 minutes or more during this operating day was 42.3%.

We also look at the time of day when the rescheduling algorithm assigns large delays. The number of delayed departures according to the OTP metric for each hour is shown in Table 3. In this scenario, most of the assigned delays are lower than ten minutes. Delays equal to or higher than 15 minutes are mainly observed during the morning, especially at 10am. Since passenger delays are higher during the beginning of the disruption, the optimal ILP solving tends to assign larger delays to departure aircraft during the morning. Therefore, a higher number of delays equal to or larger than 15 minutes can be observed at 10am and 11am.

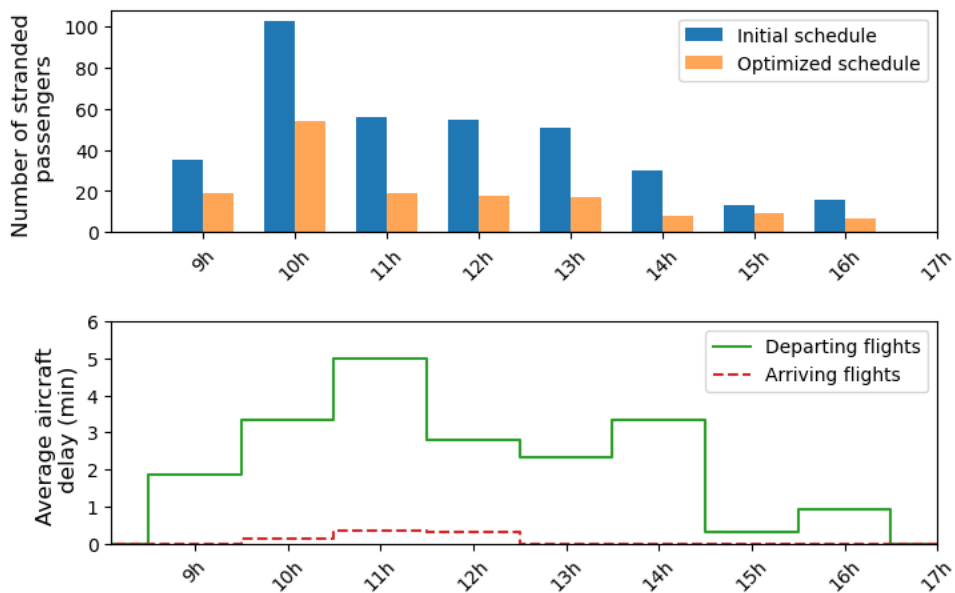


Fig. 9: Evolution in the number of stranded passengers and the average aircraft delay assigned during the disruption. The blue and orange bars on the top figure represent the number of stranded passengers per hour before and after rescheduling, respectively. The bottom figure represents the average delay assigned to the arrival and departure flight set per hour in red and green, respectively.

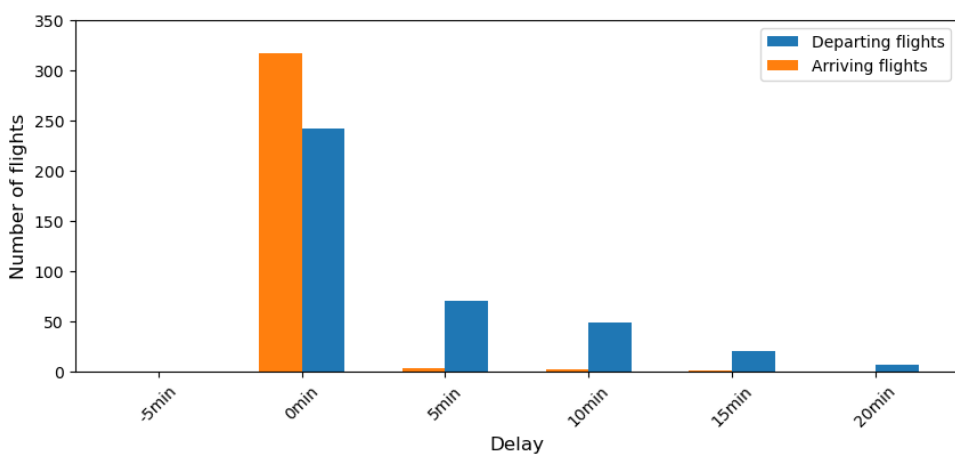


Fig. 10: Number of flights depending on the assigned delay after rescheduling. A distinction is made between departing flights (in blue) and arriving flights (in orange).

Table 3 Number of delayed flights regarding OTP metric after rescheduling

Hour	9h	10h	11h	12h	13h	14h	15h	16h
Number of delays ≥ 15 min	1	4	2	1	0	2	0	0
Number of departing flights	48	66	31	57	60	36	47	43
Share (%)	2.1	6.1	6.4	1.8	0	5.6	0	0

We also compare how the online approach performs with a single time-window approach that could be launched in a perfect world, where all data are known at the beginning of the day. Interestingly, the online solving approach provides a solution performing as well as the single-time window resolution on each criterion of the objective function. However, the online resolution performance decreases if the shifting time between two ILP solving increases. Indeed, lengthening the shifting time between two time window resolutions leads to ‘freezing’ more decision variable values obtained in the first time window solving. However, these values can be sub-optimal when new data are considered on the next time window resolution. For instance, if the shifting time window is increased from 30 minutes to 60 minutes, a 2% degradation of the objective function is observed for the whole day.

7.2.2. Comparison of the different scenarios

Table 4 presents results on the different disruptive scenarios. First, one can see that each disruption impacts passengers differently. As expected, scenarios associated with a high delay, i.e. labelled ‘X90’, generate more stranded passengers than ‘moderate’ disruptions related to the same disrupted mode, i.e. labelled ‘X45’. A disruption on a train has a higher impact compared to the other modes since, in the considered disruption modelling, all train passengers suffer from the highest delay. As a reminder, the delay experienced by train passengers is constant during the day since we assume that, for this mode, passengers do not have re-routing options. Scenario S45_3 generates the fourth highest number of stranded passengers since the associated disruption lasts longer than the other scenarios. The performance of the ILP-solving approach in the stranded passenger reduction is quite close across the different scenarios, ranging from 55% to 64%, except for scenario T90. Indeed, for this scenario, only a 22% reduction is observed. Since all train passengers affected by the disruption suffered a 90-minute delay, authorising a 20-minute deviation of the departure flight time may not be sufficient for most of the delayed passengers.

Regarding the flight delay, it increases depending on the severity of the disruption, whether by a larger passenger delay or an increased duration of the disruption, as in scenario S45_3. An exception can be noted for scenario T90, where the delay is lower than for scenario T45. For scenario T90, most stranded passengers arrive at the gate at least 20 minutes later than the boarding closure time. In this context, the exact ILP solving tends to assign lower delays since these passengers are stranded in any case. A similar observation can be made for the last criterion, which quantifies the number of delayed flights regarding the OTP metric. In general, the higher the disruption severity, the more the ILP-solving approach assigns flight delays higher than 10 minutes. There is an exception when most delayed passengers arrive at the gate 20 minutes later than the initial departure time, such as in scenario T90. In that case, the rescheduling assigns a fewer number of 15-minute and 20-minute delays.

The last column quantifies the propagated delay due to the rescheduling operated during the disruption. As observed, the effect is very limited on the remaining planning. The total propagated delay assigned across the flight set is usually lower than five minutes. The largest propagated delays are found

Table 4 Results obtained on the different scenarios through the optimal ILP solving approach.

Scenario	Initial number of stranded passenger	Relative stranded passenger reduction	Average ^{*1} delay		Number of delays \geq 15 minutes	Total propagate delay ^{*2}
			per arrival flight	per departure flight		
S45	359	57.94%	0.1min	2.5min	10	0min
S90	770	55.58%	0.5min	4.3min	32	0min
T45	1050	61.24%	1.0min	6.3min	67	40min
T90	2508	21.65%	0.7min	5.0min	54	5min
R45	750	60.67%	0.4min	4.5min	29	10min
R90	1855	60.27%	1.2min	7.3min	79	0min
S45_1	137	59.12%	0.1min	1.9min	1	45min
S45_2	188	63.83%	0.3min	2.2min	5	5min
S45_3	913	63.31%	0.2min	3.6min	34	5min

*1: Values have been computed only between the starting and ending time of the disruption. Thus, passengers stranded outside the disruption times are not considered here. *2: Propagate delays are the ones assigned to flights planned after the end of the disruption due to resource overload implying delay next arrival flights).

for S45_1. This scenario simulates an early disruption ending at a peak hour for the airport. Consequently, more propagate delays are required to mitigate airport congestion due to the rescheduling in this scenario.

7.2.3. Effect of arrival delay constraints

As the average delay assigned to arrivals in scenario S45 is only 0.2 minutes on average, the relevance of delaying arrivals is questionable. Furthermore, at the tactical level, it is much more difficult to control the flow of arriving flights from the airport operations centre than to delay departing flights at the gate. Therefore, we run the algorithm by constraining arrivals to be on time. For scenario S45, the online solution approach failed to solve the fourth time window problem. This can be explained by the fact that the sliding time window approach makes decisions without knowing the future operations. Therefore, the algorithm initially delayed departing flights, leading to an infeasible problem, i.e. a problem where all resource capacity constraints cannot be satisfied. We also tested this on scenario R90, where higher delays are assigned to arriving flights. For this scenario, the online approach successfully reschedules flights for the whole day when arrival flights are constrained to be on time. With this constraint, 864 passengers miss their flights after rescheduling, compared to 737 when arrival flight time can deviate. This represents a 7% difference in the relative reduction in the number of passengers missing their flights. Such a difference is observed since we put pressure on CDG airport by constraining each resource closely to each scheduled occupancy. If the algorithm is run in an airport with extra resource capacity, we can assume that the difference would be less significant.

7.2.4. Impact of the rescheduling on buffer time for connecting passengers

The rescheduling algorithm takes into account the transfer time of connecting passengers to ensure a minimum transfer time between flights. However, the closer the actual transfer time is to the minimum one, the greater the pressure on passengers. Therefore, we also examine the impact of flight rescheduling

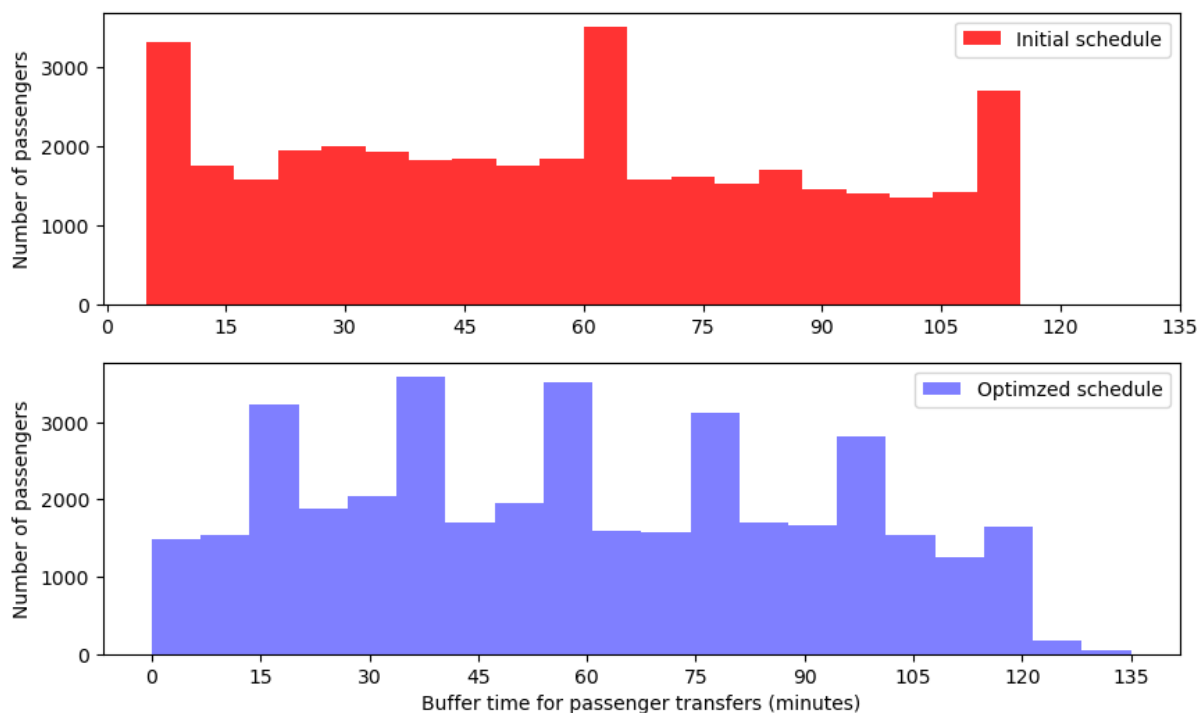


Fig. 11: Comparison of buffer time for connecting passengers before and after rescheduling, in red and blue respectively

on the buffer times for passenger transfers, i.e. the actual transfer time minus the minimum one. Fig.11 shows the distribution of buffer times for passenger transfers before and after rescheduling.

As observed in this figure, the flight rescheduling has a limited impact on connecting passengers' buffer time. The average buffer time increases from 57 minutes to 59 minutes. The distribution of buffer times is more spread after the rescheduling. Initially, the minimum and maximum buffer times are 5 and 110 minutes, respectively. After rescheduling, 1500 passengers experienced transfers with no buffer time and about 300 passengers experienced buffers of 2 hours or more. This can be interpreted as a decrease in the level of service provided to air-connecting passengers. However, such degradation is offset by the reduction in the number of passengers missing their flights thanks to the rescheduling. Future work could explore trade-offs by imposing minimum or maximum buffer time constraints during the rescheduling.

8. Conclusion

This work is a first step to filling the gap in the design of a reliable long-range multimodal transportation network for passengers. We highlighted the potential benefits that could be obtained from a passenger perspective by efficient information sharing between transportation stakeholders during airport access

mode disruption. We proposed an ILP model to optimize the flight schedule at the tactical level. An objective function has been introduced to reschedule flights regarding different criteria. Depending on airport operators' priority, it can either favour the minimisation of the number of stranded passengers, the total delay applied to the flight set or the OTP criterion. A study case around CDG airport combining various data sets has been implemented, with a release of public instances available through reference (Scozzaro, 2023)).

Results show that including information from the ground side could significantly help the airport operation centre in its decisions to limit the impact of an airport access mode disruption on passengers. Regarding the different disruptive scenarios considered, authorising a maximum delay of 20 minutes would significantly help to reduce the number of stranded passengers. The rescheduling approach succeeds in reducing around 60% the total number of stranded passengers with an average delay remaining lower than 1.2min and 7.3min for arrivals and departures, respectively. Moreover, most of the flights remain on time regarding the OTP metric. We also proposed a heuristic to compare results obtained with the ILP-solving approach. The heuristic-solving approach provides an alternative tool that already significantly reduces the number of stranded passengers. However, it tends to assign larger delays than the optimal ILP solution. Moreover, the ILP solving is fast enough to reschedule flights at a tactical level. The analyses conducted around the different disruptive scenarios highlight that during a day when passengers are severely delayed (such as scenario T90), other coordination mechanisms should be launched since moderate aircraft delays are not sufficient to wait for delayed passengers. In this situation, a large ground delay program would be more suitable.

Different research tracks should be investigated. First, a focus on passengers who are still stranded after the rescheduling should be done to see how they can be re-accommodated on other flights. Also, the integration of the security process in the problem modelling would be valuable to improve the passenger arrival modelling at the departure gate. Indeed, passengers can face large waiting times at the security screening system and thus arrive later than expected. An optimization of security screening resource allocation has been proposed in (Scozzaro et al., 2022b) to minimise passenger queuing time or the number of passengers missing their flights. An integration of both works is considered to propose a global optimization of both airport operations.

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References

- Ahmadian, M.M., Salehipour, A., 2022. Heuristics for flights arrival scheduling at airports. *International Transactions in Operational Research* 29, 4, 2316–2345.
- Bagamanova, M., Brucculeri, L., Giovannini, S., Ciaburri, M., Sangermano, V., Russo, R., Duca, G., Meincke, P.A., Maczka, M., Dziugiel, B., et al., 2022. Extended ATM for Seamless Travel (X-TEAM D2D). *EUROSIM 2021*

- Birolini, S., Jacquillat, A., Schmedeman, P., Ribeiro, N., 2023. Passenger-centric slot allocation at schedule-coordinated airports. *Transportation Science* 57, 1, 4–26.
- Bohme, D., Brucherseifer, R., Christoffels, L., 2007. Coordinated arrival departure management. In *Materiály konferencyjne 7th USA/Europe Air Traffic Management R&D Seminar, Barcelona, Hiszpania*.
- Bouarfa, S., Müller, J., Blom, H., 2018. Evaluation of a multi-agent system approach to airline disruption management. *Journal of Air Transport Management* 71, 108–118.
- Bratu, S., Barnhart, C., 2005. An analysis of passenger delays using flight operations and passenger booking data. *Air Traffic Control Quarterly* 13, 1, 1–27.
- Bueno, J., Burrieza, J., García Cantú, O., Livingston, C., Balac, M., Scozzaro, G., Buire, C., 2022. Transit final project results report.
- Buire, C., Delahaye, D., Marzuoli, A., Feron, E., Mongeau, M., 2022. Air-rail timetable synchronization for a seamless passenger journey. In *Proceedings of International Workshop on ATM/CNS 2022 International Workshop on ATM/CNS*, Electronic Navigation Research Institute, pp. 79–86.
- Buire, C., Scozzaro, G., Marzuoli, A., Feron, E., Delahaye, D., 2021. A year into the pandemic: a passenger perspective on its impact at paris-charles de gaulle airport. In *2021 IEEE International Conference on Big Data (Big Data)*, IEEE.
- Commission, E., for Mobility, D.G., Transport, for Research, D.G., Innovation, 2011. *Flightpath 2050 : Europe's vision for aviation : maintaining global leadership and serving society's needs*. Publications Office.
- De La Vega, J., Santana, M., Pureza, V., Morabito, R., Bastos, Y., Ribas, P.C., 2022. Model-based solution approach for a short-term flight rescheduling problem in aerial passenger transportation to maritime units. *International Transactions in Operational Research* 29, 6, 3400–3434.
- Delgado, L., Martín, J., Blanch, A., Cristóbal, S., 2016. Hub operations delay recovery based on cost optimisation-dynamic cost indexing and waiting for passengers strategies. In *12th SESAR Innovation Days*.
- Dell'Orco, M., Marinelli, M., Altieri, M.G., 2017. Solving the gate assignment problem through the fuzzy bee colony optimization. *Transportation Research Part C: Emerging Technologies* 80, 424–438.
- Dray, L., Marzuoli, A., Evans, A., Laplace, I., Feron, E., 2015. Air transportation and multimodal, collaborative decision making during adverse events. In *Eleventh USA/Europe Air Traffic Management Research and Development Seminar (ATM2015)*.
- Evlér, J., Asadi, E., Preis, H., Fricke, H., 2021. Airline ground operations: Optimal schedule recovery with uncertain arrival times. *Journal of Air Transport Management* 92, 102021.
- Filippi, C., Guastaroba, G., Peirano, L., Speranza, M.G., 2023. Trends in passenger transport optimisation. *International Transactions in Operational Research* 30, 6, 3057–3086.
- Guajardo, M., Rönnqvist, M., 2016. A review on cost allocation methods in collaborative transportation. *International Transactions in Operational Research* 23, 3, 371–392.
- Guimaran, D., Padrón, S., 2022. A stochastic approach for planning airport ground support resources. *International Transactions in Operational Research* 29, 6, 3316–3345.
- Gurtner, G., Delgado, L., Valput, D., 2021. An agent-based model for air transportation to capture network effects in assessing delay management mechanisms. *Transportation Research Part C: Emerging Technologies* 133, 103358.
- Hu, Y., Song, Y., Zhao, K., Xu, B., 2016. Integrated recovery of aircraft and passengers after airline operation disruption based on a grasp algorithm. *Transportation research part E: logistics and transportation review* 87, 97–112.
- Jozefowicz, N., Mancel, C., Mora-Camino, F., 2013. A heuristic approach based on shortest path problems for integrated flight, aircraft, and passenger rescheduling under disruptions. *Journal of the Operational Research Society* 64, 384–395.
- Khadilkar, H., Balakrishnan, H., 2015. Integrated control of airport and terminal airspace operations. *IEEE Transactions on Control Systems Technology* 24, 1, 216–225.
- Kim, S.H., Feron, E., Clarke, J.P., Marzuoli, A., Delahaye, D., 2017. Airport gate scheduling for passengers, aircraft, and operations. *Journal of Air Transportation* 25, 4, 109–114.
- Kjenstad, D., Mannino, C., Nordlander, T.E., Schittekat, P., Smedsrud, M., 2013. Optimizing AMAN-SMAN-DMAN at Hamburg and Arlanda airport. *Proceedings of the SID, Stockholm*
- Leng, N., Corman, F., 2020. The role of information availability to passengers in public transport disruptions: An agent-based simulation approach. *Transportation Research Part A: Policy and Practice* 133, 214–236.
- Liu, T., Cats, O., Gkiotsalitis, K., 2021. A review of public transport transfer coordination at the tactical planning phase. *Transportation Research Part C: Emerging Technologies* 133, 103450.
- Ma, J., Delahaye, D., Sbihi, M., Scala, P., Mota, M.A.M., 2019. Integrated optimization of terminal maneuvering area and

- airport at the macroscopic level. *Transportation research part C: Emerging technologies* 98, 338–357.
- Ma, J., Sbihi, M., Delahaye, D., 2021. Optimization of departure runway scheduling incorporating arrival crossings. *International Transactions in Operational Research* 28, 2, 615–637.
- Marzuoli, A., Boidot, E., Feron, E., van Erp, P.B., Ucko, A., Bayen, A., Hansen, M., 2015. Multimodal impact analysis of an airside catastrophic event: A case study of the asiana crash. *IEEE Transactions on Intelligent Transportation Systems* 17, 2, 587–604.
- Montlaur, A., Delgado, L., 2017. Flight and passenger delay assignment optimization strategies. *Transportation Research Part C: Emerging Technologies* 81, 99–117.
- Mota, M.M., Scala, P., Herranz, R., Schultz, M., Jimenez, E., 2020. Creating the future airport passenger experience: Imhotep. In *European Modelling Simulation Symposium, Athens, Greece*.
- OAG, 2023. What is on time performance (otp)? <https://www.oag.com/on-time-performance-airlines-airports>.
- Paris Aéroport, 2022. Check-in procedures. <https://www.parisaeroport.fr/en/passengers/flight-preparation/check-in>.
- Paul, A., 2020. Modelling and assessing the role of air transport in an integrated, intermodal transport system. <https://modus-project.eu/>.
- Paulsen, M., Rasmussen, T.K., Nielsen, O.A., 2021. Impacts of real-time information levels in public transport: A large-scale case study using an adaptive passenger path choice model. *Transportation Research Part A: Policy and Practice* 148, 155–182.
- Pujet, N., 1999. Modeling and control of the departure process of congested airports. Ph.D. thesis, Massachusetts Institute of Technology.
- Rahimi Mazrae Shahi, M., Fallah Mehdipour, E., Amiri, M., 2016. Optimization using simulation and response surface methodology with an application on subway train scheduling. *International Transactions in Operational Research* 23, 4, 797–811.
- Rothe, H., Mota, M., Scala, P., Jimenez Perez, E., Herranz, R., Fricke, H., Casas, J., Rothe, H., Jimenez Perez, E., Herranz, R., et al., 2022. Integrated multimodal airport operations for efficient passenger flow management—two case studies. In *SESAR Innovation Days 2022*.
- Scozzaro, G., 2023. Données publiques @recherche.enac.fr. <http://data.recherche.enac.fr/scozzaro/pfrsp/>.
- Scozzaro, G., Ma, J., Delahaye, D., Feron, E., Mancel, C., 2022a. Flight rescheduling to improve passenger journey during airport access mode disruptions. In *International Conference on Research in Air Transportation (ICRAT 2022)*.
- Scozzaro, G., Mancel, C., Delahaye, D., Feron, E., 2022b. Optimising security screening resources during airport access mode disruptions. In *12th SESAR Innovation Days*.
- Siegrist, M., Corman, F., 2020. Quantifying the heterogeneity of direct and indirect effects of a public transport disruption with agent-based simulation. In *20th Swiss Transport Research Conference (STRC 2020)(virtual)*, STRC.
- SNCF, 2019. Horaire des tgv. <https://ressources.data.sncf.com/pages/accueil/>.
- W Axhausen, K., Horni, A., Nagel, K., 2016. *The multi-agent transport simulation MATSim*. Ubiquity Press.
- Yu, X., Miao, H., Bayram, A., Yu, M., Chen, X., 2021. Optimal routing of multimodal mobility systems with ride-sharing. *International Transactions in Operational Research* 28, 3, 1164–1189.